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Complete List of Authors:	Campion, Mitchell; UND, Electrical Engineering Ranganathan, Prakash; University of North Dakota, Electrical Engineering Faruque, Saleh; University of North Dakota, Electrical Engineering
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UAV Swarm Communication and Control Architectures: A Review

Mitch Campion, Prakash Ranganathan, and Saleh Faruque
Department of Electrical Engineering
University of North Dakota
Grand Forks, ND 58202
Prakash.ranganathan@engr.und.edu

***Abstract*—Unmanned aerial vehicles (UAVs) have significantly disrupted the aviation industry. As technology and policy continue to develop, this disruption is only going to increase in magnitude. A specific technology poised to escalate this disruption is UAV swarm. UAV swarm has the potential to distribute tasks and coordinate operation of many UAVs with little to no operator intervention. This paper surveys literature regarding UAV swarm and proposes a swarm architecture that will allow for higher levels of swarm autonomy and reliability by utilizing cellular mobile wireless communication infrastructure. This paper chronicles initial testbed development to meet this proposed architecture. Focused development of UAV swarms with UAV-to-UAV communication autonomous coordination ability is central to advancing the utility of UAV swarms. The use of cellular mobile framework alleviates many limiting factors that hinder the utility of UAVs including range of communication, networking challenges, and size-weight-and-power (SWaP) considerations. In addition, cellular networks leverage a robust and reliable infrastructure for machine to machine (M2M) communication proposed by 5G systems.**

Keywords: **autonomous systems, UAV swarm, wireless communications**

I. Introduction

Small unmanned aircraft systems (sUAS) have become an attractive vehicle for a myriad of commercial uses. The ability of sUAS to bring payloads for utility, sensing, and other uses into the sky without a human pilot on board is an attractive proposition. With manned aviation, there is the risk of injury or fatality should a critical error occur in flight. With an unmanned aircraft system, these concerns are alleviated. Manned aviation is expensive. The price to purchase or rent a general aviation aircraft is prohibitive. Pilot labor, fuel costs, and maintenance are prohibitive expenses to the use of general aviation aircraft for widespread commercial applications. For these reasons, the utility of sUAS has been an attractive alternative. There are also many advantages for unmanned aircraft in military applications, however, this paper focuses predominantly on private sector commercial applications.

A. State of the industry

In August of 2016 the regulatory body of aviation in the United States announced the passing of 14 CFR Part 107, a federal code of regulations for the commercial use of sUAS (Duncan 2016). This code established a regulatory framework for the widespread commercial use of sUAS in the United States National Airspace System (NAS). The passing of part 107 was significant, in that it laid foundational regulations for widespread commercial use of sUAS. It also relaxed many regulations and requirements that were in place for the commercial use of sUAS prior to part 107 that imposed barriers to market entry for basic commercial operations. Since the adoption of part 107 regulations, the number of registered commercial sUAS pilots has grown to over 60,000 as of September 2017 (Bellamy 2017) . The FAA estimated that 600,000 commercial sUAS would fly in the year following the passing of 14 CFR Part 107 in August 2016 (Jansen 2016).

The sUAS industry has oriented itself mostly as a service industry. The actual sUAS themselves are important, but the real value of the sUAS is the type of payloads they can carry and what type of services they can efficiently provide. Some of these use-cases include photography, cinematography (Canis 2015), precision agriculture (Primicerio et al. 2012), power line and structure inspection (Jones 2005; Morgenthal et al. 2014), surveillance security (Canis 2015), surveying (Chisholm et al. 2013), Infra-red and multispectral imaging (Turner et al. 2010; Previtali et al. 2013; Bendig et al. 2015; Vega et al. 2015), natural disaster recover (Neto et al. 2012), search and rescue operations (Rudol 2008) and many more (Canis 2015).

B. Traditional commercial operation

Currently, as per the regulations of 14 CFR part 107.35, "A person may not operate or act as a remote pilot in command or visual observer in the operation of more than one unmanned aircraft at the same time". This regulation, coupled with others in part 107 currently make the simultaneous commercial operation of UAVs illegal under part 107 operations. The current method of commercial operations is for one pilot to control one UAS while other crew members act as mission control or visual observers. The hardware involved in a traditional operation includes a handheld transmitter to control an UAV, associated payload(s), and a computer with ground control software acting as a ground control station (GCS) for semi-autonomous control (Canis 2015; Duncan 2016). Fig. 1 shows a block diagram of hardware for traditional commercial applications.

II. Current state of swarm

Though the utility of sUAS has budded a growing industry, the capability of swarms of UAVs is an intriguing development that is only in its infancy. Limitations to traditional operation of sUAS are that they have a limited payload, limited flight time, and require a remote pilot to operate them through a handheld transmitter or computer with appropriate control software. Coordinating multiple UAVs to perform tasks in a swarm environment is attractive because it addresses the limitations of a single sUAS while adding more functionality.

A swarm is generally defined as a group of behaving entities that together coordinate to produce a significant or desired result (Teague 2008; Bürkle 2011; Jeffrey 2015). There are several natural examples of swarming behavior in nature. Bees coordinate with one another to complete tasks critical to the survival of their swarm. Flocks of migrating geese coordinate efficient flight patterns to achieve their migration. Similarly, a swarm of UAVs is a coordinated unit of UAVs that perform a desired task or set of tasks. A general architecture for task order in swarm environments is shown in the literature (Jeffrey 2015). A UAV swarm is an example of this architecture and could complete tasks relevant to commercial purposes.

A. Advantages and applications

Advantages to swarm include time-savings, reduction in man-hours, reduction in labor, and a reduction in other associated operational expenses. One specific example of a commercial application that would benefit from UAV swarm is the observation of normalized difference vegetation index (NDVI). NDVI is an important observation for precision agriculture. NDVI observation requires flying sUAS over farmland. Cameras equipped with remote sensing equipment record high resolution geo-tagged imagery of crops. NDVI imagery and sensing equipment show what parts of fields of crops are in the proper or improper stages of development. Surveying a farm with hundreds or thousands of acres is time-consuming and lacks efficiency using current methods. The use of a coordinated number of sUAS surveying an entire farmstead with little to no operator intervention would greatly increase efficiency and could revolutionize precision agriculture.

The most notable application of UAV swarm is delivery services. Amazon and United Postal Service have indicated interest in using UAS for package delivery (Amazon 2017; MacFarland 2017). Using a typical remote pilot and a single sUAS, package delivery would be inefficient. Swarms of UAVs with coordinated control and communication capabilities would be efficient in this application.

B. Autonomy in UAS

There are varying levels of autonomy for autonomous vehicles. Levels of autonomy are based on the number of tasks, coordination, or decision making a vehicle can make without input from an operator. In the example of commercial and passenger vehicles, 6 levels have been defined. The six levels range from no autonomy, to full autonomy where a steering wheel is optional (Huang et al. 2007; SAE 2016). Levels of autonomy for UAVs are not yet well defined (Roberts-Grey 2015). A proposal was made for five levels of UAV control autonomy (Huang 2008), but these levels are not widely accepted and require more research to arrive at a clear consensus (Protti 2007). Following the recommendations of these works, the highest level of UAV swarm autonomy is defined as the ability to perform a task coordinated among multiple UAVs without intervention of human operator.

This level of autonomy can be achieved by a UAV swarm. A UAV swarm is a cyber-physical system (CPS). The most important aspect of an autonomous system is the decision chain that occurs in lieu of human operation. The movement and task completion of a traditionally operated UAV is completely controlled by the decisions made by a human, whereas in a fully autonomous system, decisions are made by algorithms. An autonomous CPS uses a decision-making paradigm defined by three stages: Data, control, and process. The decision structure of a UAV swarm would follow this paradigm as proposed in (Plathottam et al. 2018) and shown in Fig. 2.

Sensors are the hardware of data stage of the paradigm for UAV swarm. Sensors acquire raw data pertaining to the environment of operation of a desired task and relay the data to a computer. Sensors specific to UAV swarm environments may include GPS, airspeed sensors, acoustic sensors, cameras, and many more depending upon the application. The control stage is comprised of 2 sub-phases: perception and planning. Perception is defined as the act of transforming ambiguous data to useful information. Planning refers to the process of using the perceived information to formulate a decision to execute a task. The perception and planning phases are key phases where algorithm development is necessary and ultimately where autonomy is realized. The work in (Plathottam et al. 2018) surveys and proposes methods centered upon artificial intelligence, machine learning, formal logic, expert systems, and other distributed intelligence methods to ultimately realize full autonomy in distributed CPS like UAV swarms. NVIDIA has recently designed specific embedded hardware for autonomous vehicles to meet this need (NVIDIA 2017; Smolyanskiy et al. 2017) and finally, the process stage is the execution of the decisions made and the completion of the task.

C. Autonomous swarm control (ASC)

Perception Phase. The importance of algorithms in autonomous vehicle environments cannot be understated. In lieu of human operation, the control of UAV swarms is left to algorithms. Algorithms that control swarm operation inhabit the control stage of the autonomous decision-making paradigm. Algorithms are an essential part of both perception and planning phases of the control stage. In this perception phase, the role of algorithms is to process the data that is acquired by the sensors that inform of system parameters. Challenges arise in processing high volume of data from many on-board sensors. The algorithms in this sub-phase often are data mining or data processing algorithms and perform the cleaning and organizing the large amount of sensor data (Pophale 2016). The authors in (Yong et al. 2017) proposed a kernel principal components (KPCA) algorithm to detect anomalous sensor data from on board a UAV. Principal components analysis is a well-known method for observing correlations between data streams and dimensionality reduction of data. In (Yong et al. 2017), the use of KPCA for UAV sensor data is novel and appreciable. More research needs to be done in this area, but algorithms for anomaly detection, fault detection, and dimensionality reduction need to be developed for UAV specific applications.

Planning Phase. In this phase, algorithms take the processed data and turn it into meaningful information. There are many different types of algorithms that have been demonstrated to perform this task in cyber physical systems (CPS) like UAV swarm. Within the planning phase, information required for UAV tasks are formulated. Due to the complexity of UAV systems and the highly specific nature of UAV applications, there is a need of novel algorithms that could be deployed to turn clean sensor data into actionable information on board the UAV. Some types of algorithms that have been proposed are formal logic (Nilsson 1991) machine learning/neural network (Domingos 2015), and graph theory (Diestel 1997; Russell 2010) and (Plathottam et al. 2018). A simple algorithm that is already commonly deployed by UAV flight control systems and GCS for navigation is the Kalman Filter (Jung 2007; Mao et al. 2007). Machine learning methods have been proposed for detection of safe landing zones in emergency landing situations (Li 2013; Guo et al. 2014). All of these methods are important for further development of UAV technology.

The UAV swarm environment poses specific challenges, therefore careful selection and development of algorithms are required for its suitability. Specifically, the autonomous control of many UAVs in a safe and efficient scheme is of utmost importance. There are number of proposed methods for swarm control algorithms. Perhaps the most common algorithm proposed for UAV swarm control and planning revolves around variations and adaptions of particle swarm optimization (Hassan et al. 2012; Roberge et al. 2013; Fu 2012; Duan et al. 2013) . Though there are no existing works for these methods, we propose the use of linear programming methods for path optimization as well as implementations of bee colony algorithms for optimized path planning and coordination among UAVs as described generically in (Karaboga et al. 2007; Karaboga et al. 2014) and briefly for UAV applications in (Roberge et al. 2013). The authors in (De Souza et al. 2015) addressed the use of 3G/4G networks for M2M swarm communication environments and simulated a bandwidth efficient coordination algorithm in this environment. To date, the work by De Souza et al. (De Souza et al. 2015) is the only known work proposing and simulating a wireless network infrastructure and examining the control architecture for UAV swarms. Some algorithms and methods for UAV swarm control have been proposed and demonstrated in simulated environments. In general, there are limited literature exists, where autonomous operation of UAV swarms are truly demonstrated, though many exist in simulated environments.

D. Current swarm communication architectures

Swarm itself, is not necessarily a new technology. There have been proposed applications and development of UAV swarm, particularly for military applications, dating back to the early 1990's (Kelly 1994; Andrew 2017; Condliffe 2017). Despite this, UAV swarm is still in its infancy. As technology has developed and become more accessible, research, development, and integration efforts for sUAS swarm in more widespread and commercial applications have started to attract attention. Notably, a swarm of 300 drones developed by Intel was deployed as a coordinated light show for super bowl 51 as well as the 2018 Winter Olympics (Molina 2017). In addition to these examples, there have been other demonstrations of UAV swarm, however, in most demonstrations the level of autonomous operation has been relatively low.

In most cases each individual UAV is simultaneously controlled by a GCS. Traditional UAV swarms use a computer as a GCS running a ground control software. The computers are equipped with a transceiver that sends and receives telemetry data from connected UAVs. Telemetry data traditionally includes GPS information, groundspeed, and other parameters collected from payload sensors. Traditionally these transceivers use unlicensed Radio Frequency (RF) bands such as 900MHz to send and receive the data. Higher levels of autonomy would allow UAVs to make decisions using on-board computers. Current demonstrations of

UAV swarm utilize one of two general forms of swarm communication architecture. The two forms are an infrastructure-based swarm architecture and ad-hoc network-based architecture.

1) Infrastructure based swarm architecture

The infrastructure-based architecture consists of a ground control station (GCS) that receives telemetry information from all drones in the swarm and sends commands back to each UAV individually. In some cases, the GCS communicates back to individual drones in real time, sending commands to the flight controllers on board each UAV. In other cases, a flight operation is pre-programmed aboard each UAV which is simultaneously operated while the GCS is simply used to observe the systems. These UAV swarms are considered to be semi-autonomous as they still require direction from a central control to complete an assigned operation (Bekmezci et al. 2013).

Infrastructure based swarm architecture is the most common architecture for UAV swarms (Bekmezci et al. 2013). Some commonly used and readily available GCS software contain basic infrastructure-based swarm capabilities (Ardupilot 2018). One advantage of infrastructure-based swarming is that optimization and computations can be conducted in real time by a GCS via a higher performance computer that could reasonably be carried on a sUAS. Additionally, networking between drones is not necessary, which results in a reduction of required payload (Bekmezci et al. 2013; Sivakumar et al. 2010).

Infrastructure-based swarm architectures are dependent upon the GCS for coordination of all drones. This dependency causes a lack of system redundancy. In the event of an attack or failure to any operation of the GCS, the operability of the entire swarm is compromised. Infrastructure-based methods require all UAVs to be within propagation range of the GCS. A drawback to unlicensed RF communications is that communication may be susceptible to interference.

Due to the light payload capacities of sUAS, the hardware necessary to establish reliable communication with an infrastructure may limit the utility of infrastructure-based swarms. Another drawback is a lack of distributed decision making. In an infrastructure-based architecture, the GCS coordinates the decision making of all UAVs based on computations and algorithms developed in the GCS. Fig. 3. demonstrates the infrastructure-based swarm architecture.

2) Flying ad-hoc network (FANET) architecture

In (Bekmezci et al. 2013) the use of Flying Ad-Hoc Networks (FANETs) to coordinate communication between all drones in a network is proposed. FANETs (Flying Ad-hoc Networks) is a group of Unmanned Air Vehicle (UAVs) communicating with each other with no need to access point, but at least one of them must be connected to a ground base or satellite. UAVs carry out their missions without human help, like an autopilot. In recent years, many research fields from academia and industry make attention on FANETs due to cheaper and smaller wireless communicating devices. Now, FANETs are used in various applications such as military and civil applications, managing wildfire and disaster monitoring. As each type of network has its own specification, it is important to use a reliable protocol based on the specification and check its performance using simulation. Two factors affect protocol simulation: the first one is mobility model, and the second one is the communicating traffic pattern, among others.

A wireless ad-hoc network (WANET) is a wireless network that does not rely on existing infrastructure to establish the network. No routers or access points are needed for an ad-hoc network. Instead, nodes are dynamically assigned and reassigned based on dynamic routing algorithms. Various configurations of ad-hoc communication networks have been proposed in machine to machine communication systems (Walter et al. 2006; Lamont et al. 2007; Teague et al. 2008; Elston et al. 2009; Bürkle et al. 2011; Sahingoz 2014). In a FANET, all UAVs are part of a network of communications that is established between the UAVs. This network allows for real time communications between UAVs as shown in Fig. 4.

Direct communication between UAVs forces distributed decision making because it is not a necessity for an infrastructure-based decision engine. This also provides built in redundancy as the entire swarm is not dependent upon an infrastructure to execute the desired operation. This is a primary advantage of FANETs. Some drawbacks to FANETs are related to SWaP considerations.

To establish a FANET, networking hardware is required on board each UAV. The distance over which UAVs can reliably communicate to one another in a FANET is a limiting factor to its implementation (Bekmezci et al. 2013; Sahingoz et al. 2014). Dynamic reconfiguration of routing for UAV swarm applications is a challenging task resulting packet loss (Zhou et al. 2012; Bekmezci et al. 2013) . For applications where accurate telemetry of data between UAVs is critical, the establishment of a reliable FANET is a difficult (Bekmezci et al. 2013; Sahingoz et al. 2014). This work proposes a hybrid of an infrastructure-based network making use of cellular wireless communications infrastructure but establishing network protocol between drones without intervention of a GCS. This proposed architecture of UAV swarms leverages strengths of both architectures while mitigating some weaknesses.

In (De Souza et al. 2015), the authors discusses the problem of UAV swarm formation and maintenance in areas covered by such mobile network, and propose a bandwidth-efficient multi-robot coordination algorithm for these settings. In (Lin 2005; Arques 2013; Brust 2015) the authors discuses swarm behaviors for search and rescue tasks (e.g., forest conditions) using and agent-oriented platforms for multi-robot environments. Specifically in (Brust 2015), authors consider the problem of establishing an efficient swarm movement model and a network topology between a collection of UAVs, which are specifically deployed for the scenario of high-quality forest-mapping. They propose a novel solution to the formation flight problem for UAV swarms. For example, the forest environment with its highly heterogeneous distribution of trees and obstacles represents an extreme challenge for a UAV swarm. It requires the swarm to constantly avoid possible collisions with trees, to change autonomously the trajectory, which can lead to disconnection to the swarm, and to reconnect to the swarm after passing the obstacle, while continue collecting environmental data that needs to be fused and assessed efficiently. In (Varadharajan 2017), the authors discusses micro UAS swarms for seamless coordination. Here, a platform for the creation of such swarms is presented. It is based on commercially available quadrocopters enhanced with on-board processing and communication units enabling full autonomy of individual drones. Furthermore, a generic ground control station is presented that serves as integration platform. In (Gupta 2015) authors surveys outstanding issues in communication protocols, network layers, and energy challenges in UAV swarms leading to a new class of networks.

III. Proposed Swarm Architecture

The proposed architecture is an adaptation of an ad-hoc network realized through infrastructure support. Specifically, the infrastructure features complete UAV-to-UAV communication, where the telemetry of each UAV is communicated to every other UAV via cellular mobile infrastructure as shown in Fig. 5. In this architecture, decisions are distributed among the UAVs, and the infrastructure is purely used to transmit data.

High levels of autonomy can still be achieved despite distributed nature of the proposed infrastructure-based architecture. UAV payloads containing computational power sufficient to coordinate decisions based on the real-time telemetry data received from connected all UAVs shall be deployed. This allows for distributed decision making based upon formal logic, machine learning, and other distributed control algorithms as proposed in (Plathottam et al. 2018) and discussed previously in this work. The command and control of single UAV using cellular network infrastructure has been proposed in (ATT 2016; Qualcomm 2016) and technologies to stream camera data for UAVs through cellular networks has been demonstrated by (Botlink 2017).

A. Machine to Machine (M2M) and 5G networks

Fourth generation (4G) cellular technology boasts maximum download speeds of 1Gbps (OpenSignal News 2014). 5G communication systems are expected to boast maximum download speeds of 10Gbps with network latency as low as 1ms. A typical packet size for UAV communications is between 17 and 263 bytes. While 4G speeds are sufficient for these packets, 5G will allow for additional data streaming including data types such as video from payload cameras or data from payload light detection and ranging (LiDAR) systems. The ability to achieve low latency is important for UAV swarm communication. A central objective to 5G communications is machine to machine (M2M) communications (Boccardi 2014; Shariatmadari 2015). M2M communication capabilities of 5G would provide a natural backbone for UAV swarm environments (Demestichas 2013; Agiwal 2016). The ability to transmit real-time telemetry data between all UAVs connected to the cellular network enables detect and avoid (DAA) methodologies. The hardware required to reliably access cellular networks is space and weight efficient. SIM cards or wireless access cards are lightweight, weighing just a few grams, and can easily be added to a companion computer or even a companion smart phone (Xcraft 2017). Analysis of communication latency using the proposed infrastructure is a topic of research. However, packet loss and the performance of orthogonal frequency-division multiplexing (OFDM) for UAV communication have been analyzed and with increased speeds and infrastructure updates of 5G systems, the performance will increase (Wu et al. 2005; Zhou et al. 2012).

B. Strengths of proposed architecture

The advantages of this architecture are many. First, the range for which the UAVs can communicate is practically unlimited. Nearly the entirety of the United States has 3G or better cellular data coverage with speed ever increasing. The reliability and redundancy of mobile network for UAV swarm are less of a concern than for traditional infrastructure reliant UAV swarm architecture due to the inherent reliability of cellular base stations. While high levels of autonomy can be achieved through traditional architectures, the redundancy provided by the proposed infrastructure is advantageous in comparison.

IV. Preliminary Development

A need for counter autonomous UAV technology has driven development of UAV swarm technology (Ranganathan 2017). Preliminary development has focused upon developing a testbed of equipment to test UAV swarm architectures and communication structures, including the proposed cellular network-based architecture. The command and control of a single UAV using cellular network have been demonstrated in this testbed. Real time UAV-to-UAV communication including sending of basic flight commands through an ad-hoc UAV network has also been demonstrated. The ability to fly multiple UAVs that communicate with one another and coordinate movement among each other has been successfully demonstrated in this testbed environment. Specifically, demonstration of a predefined flight path has been assigned to a master UAV. When this master UAV begins the flight, networked (swarm) UAVs receive information from the master UAV as well. Based on the communicated telemetry information, swarmed UAVs have been able to execute commands to autonomously follow the master UAV on a predefined flight path without collision with any other UAV in the swarm. The use of cellular networks for UAV swarm control is not yet approved by regulatory bodies, so preliminary development focuses on establishing initial ad-hoc mesh network communication using traditional hardware that can be extended for the use of cellular network communication between UAVs via the use of virtual machines when approval is granted. Methodologies and control of UAV swarms is tested using software virtual interfaces and software/hardware in the loop protocols.

A. UAV-to-UAV network communication test bed

The testbed developed uses custom built quadcopters. The quadcopters feature flight controllers interfacing with on-board companion computers and mesh networking hardware. The flight controller communicates with the on-board computer using Micro Air Vehicle Link (MAVLink) communication protocol (Mavlink Protocol 2017). The companion computer understands MavLink telemetry through MavProxy software (MavProxy 2017). MAVLink is the header only, message-marshalling library used as the communication protocol between the ground station and plane. The main components of a MAVLink message are the header, system ID, message ID, and payload. The header is used to classify the message as a MAVLink packet. The system ID identifies the system sending the message while the message ID identifies the type of message being sent. For example, the most common message to send is the heartbeat (ID = 0) which is constantly sent to ensure that the plane and ground station are properly connected and communicating. The payload of the message is the content inside it. The payload can contain fields such as the vehicle type, flight mode, positioning data, or commands to execute. These messages are sent as data packets between the ground station and plane to properly fly the UAV.

The flight control stack is open source and allows for custom development of control methods. The companion computer and networking capabilities allow for the development of flight control methods based upon data that is received from other UAVs in the network. Fig. 6. displays a functional block diagram of the communication protocol from flight controller and companion computer of one UAV to the flight controller of another UAV. Currently simple tasks such as swarms of UAVs that follow each other have been demonstrated. More complex tasks and the methodologies surrounding the achievement of those will be subject of future publications. The key to this publication is the establishment of a reliable infrastructure for swarm communications. The proposition of cellular wireless infrastructure is promising in solving many limiting factors experienced in preliminary development of autonomous UAV swarm. With the proper regulatory framework and continued technology integration this architecture is promising.

V. Conclusion

This paper provides a concept level proposal, initial development, and literature review for the use of cellular networks as the communication infrastructure for UAV swarms. It provides an overview of the sUAS industry, the applications of UAV swarm, and in-house development efforts for UAV swarm. The paper reviews preliminary testbed developments and provides direction for future works regarding UAV swarm at UND. Specific development of autonomous swarms with UAV-to-UAV communication and coordination ability is central to advancing the utility of UAV swarms. Though swarm technology has yet to be practically utilized in commercial applications, there exists great potential. The use of cellular mobile framework alleviates limiting factors for traditional UAVs swarm communication approaches. The use of cellular networks for UAV swarm would greatly increase swarm efficiency and commercial utility especially in the presence of upcoming 5G networks with M2M communication capabilities.

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Figure Captions

Fig. 1. Block diagram of traditional hardware setup and control of single sUAS

Fig. 2. Decision chain of an autonomous system

Fig. 3. Block diagram of infrastructure (GCS) based swarm architecture

Fig. 4. Communication architecture of UAV swarm based on FANET

Fig. 5. Proposed cellular network UAV swarm architecture

Fig. 6. UAV-to-UAV communication hardware diagram

Fig.1

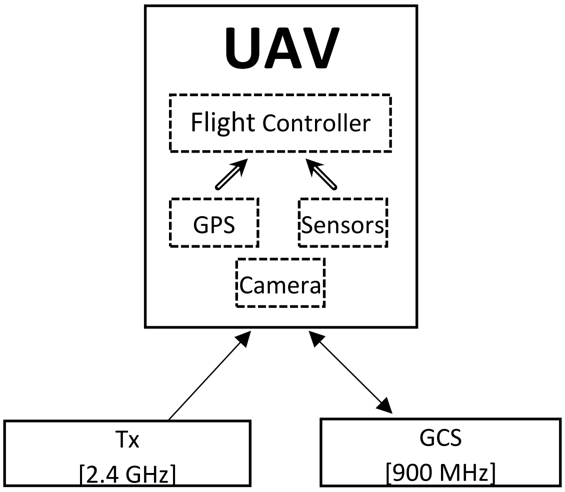

UAV
Flight Controller
GPS
Sensors
Camera
Tx
[2.4 GHz]
GCS
[900 MHz]

Fig.2

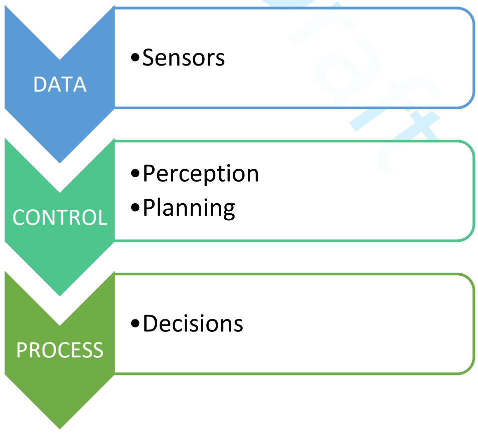

DATA
•Sensors
CONTROL
•Perception
•Planning
PROCESS
•Decisions

Fig.3:

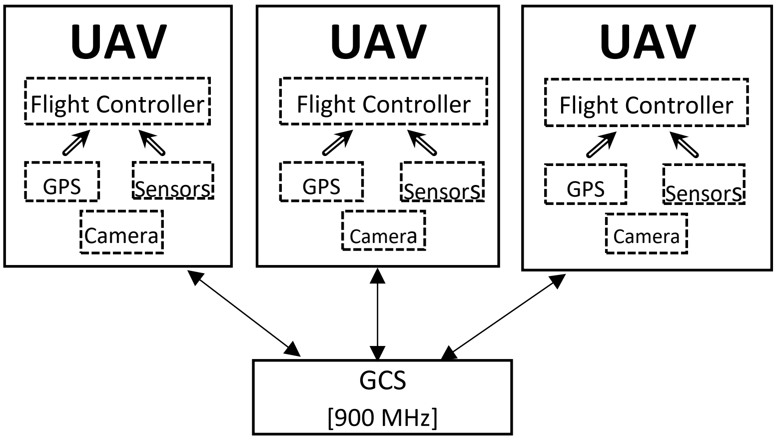
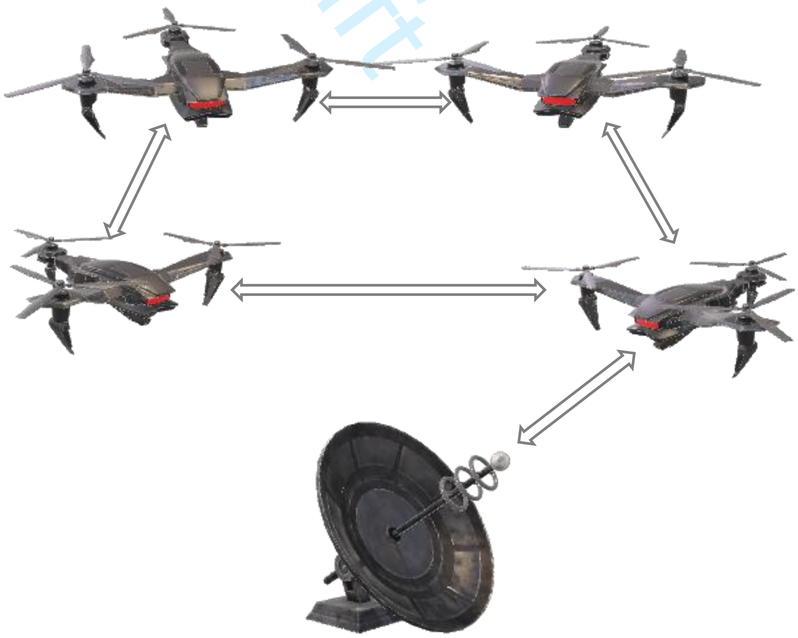

UAV
Flight Controller
GPS
Sensors
Camera
UAV
Flight Controller
GPS
SensorS
Camera
UAV
Flight Controller
GPS
SensorS
Camera
GCS
[900 MHz]

Fig.4:



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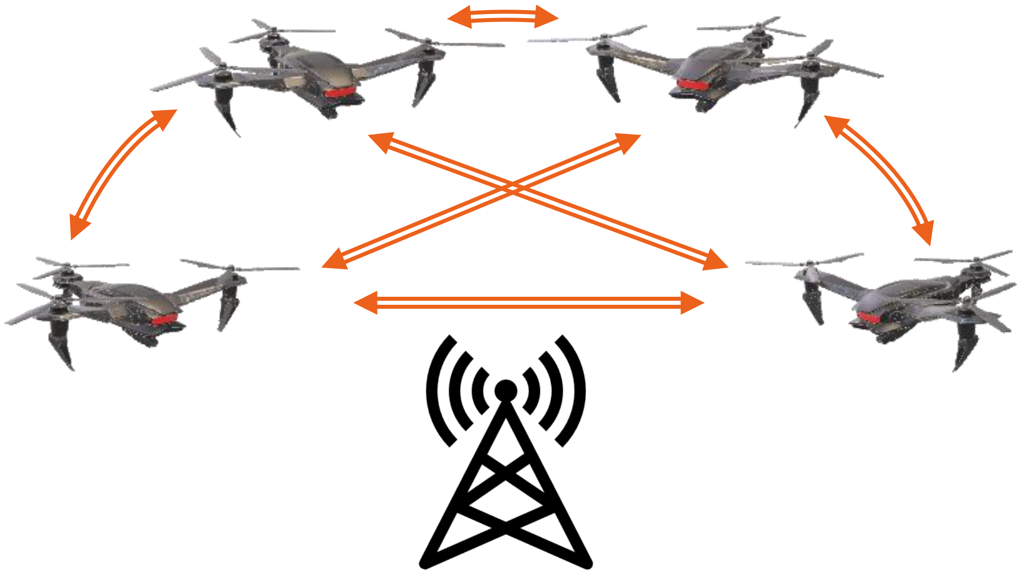

Fig. 6: